Power Grid Management in Response to Extreme Events

Rozhin Eskandarpour

University of Denver

Power Grid Management in Response to Extreme Events

Abstract

Power system management in response to extreme events is one the most important operational aspects of power systems. In this thesis, a novel Event-driven Security Constrained Unit Commitment (E-SCUC) model and a statistical method, based on regression and data mining to estimate the system components outages, are proposed. The proposed models help consider the simultaneous outage of several system components represented by an *N*-1-*m* reliability criterion and accordingly determine the proper system response. In addition, an optimal microgrid placement model with the objective of minimizing the cost of unserved energy to enhance power system resilience is proposed.

The numerical simulations on the standard IEEE 30-bus and IEEE 118-bus test systems exhibit the merits and applicability of the proposed E-SCUC model, as well as the advantages of the data mining approach in estimating component outage, and the effectiveness of the optimal microgrid placement in ensuring an economic operation under normal conditions and a resilient operation under contingency cases.

Document Type

Thesis

Degree Name

M.S.

Department

Electrical Engineering

First Advisor

Amin Khodaei, Ph.D.

Second Advisor

Kimon Valavanis

Third Advisor

Wenzhong Gao

Keywords

Extreme event, Machine learning, Microgrids, Power system resilience

Subject Categories

Electrical and Computer Engineering

POWER GRID MANAGEMENT IN RESPONSE TO EXTREME EVENTS

A Thesis

Presented to

the Faculty of the Daniel Felix Ritchie School Engineering and Computer Science

University of Denver

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

---

by

Rozhin Eskandarpour

November 2016

Advisor: Dr. Amin Khodaei

Author: Rozhin Eskandarpour
Title: POWER GRID MANAGEMENT IN RESPONSE TO EXTREME EVENTS
Advisor: Dr. Amin Khodaei
Degree Date: November 2016

ABSTRACT

Power system management in response to extreme events is one the most important operational aspects of power systems. In this thesis, a novel Event-driven Security Constrained Unit Commitment (E-SCUC) model and a statistical method, based on regression and data mining to estimate the system components outages, are proposed. The proposed models help consider the simultaneous outage of several system components represented by an N-1-m reliability criterion and accordingly determine the proper system response. In addition, an optimal microgrid placement model with the objective of minimizing the cost of unserved energy to enhance power system resilience is proposed.

The numerical simulations on the standard IEEE 30-bus and IEEE 118-bus test systems exhibit the merits and applicability of the proposed E-SCUC model, as well as the advantages of the data mining approach in estimating component outage, and the effectiveness of the optimal microgrid placement in ensuring an economic operation under normal conditions and a resilient operation under contingency cases.

ACKNOWLEDGEMENTS

One amazing scholar, one privilege opportunity, and one endless support have changed my life.

It is my greatest pleasure to acknowledge my deepest gratitude and appreciation to my advisor Dr. Amin Khodaei for supporting me in this incredible field of research and his endless commitment. I believe that it is always an excellent privilege to be under his supervision to accomplish educational achievements.

Additionally and foremost, I would like to express my sincerest appreciations to Dr. Kimon Valavanis, who is not only an excellent and knowledgeable professor but also a tactful and supportive chair that I have always admired his devotion to students.

I am also very grateful to my oral defense committee Dr. Ryan Elmore, Dr. Kimon Valavanis and Dr. Wenzhong Gao for their assistance to improve this project; and truly appreciate their time and consideration.

Last but not least, this thesis work is dedicated to my parents and my husband, Ali, who have been a constant source of support and encouragement during the challenges of this research. I truly thank them for their kind everlasting help, generous advice and support through my study.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. CHAPTER ONE: INTRODUCTION

Extreme events, including severe weather events and natural disasters, result in significant economic, social, and physical disruptions and cause considerable inconvenience for residents living in disaster areas. To address this issue, the topic of power grid resilience has gained significant attention in recent years. Power grid resilience is defined as the grid capability to withstand low-probability high-impact events by minimizing possible power outages and then quickly returning to its normal operating state.

Power system operators commonly rely on a security-constrained unit commitment (SCUC) to schedule the available generation resources needed to meet the forecasted load and addressing prevailing system constraints in response to limited components unavailability. Although widely used and proved viable, the SCUC solution cannot guarantee a useful solution when the system is subject to extreme events, i.e. severe weather events and natural disasters. In other words, even though a secure solution is obtained, the solution does not ensure the grid resilience in response to the extreme event. Considering this issue, and the growing number and intensity of extreme events, this study proposes and formulates an Event-driven SCUC (E-SCUC) model which ensures a resilient supply of loads, even in the case of multiple component outages.

An accurate estimation of the component outages, however, is of ultimate importance in ensuring a viable resource schedule. Along with the proposed E-SCUC method, a kernel density estimation method, based on regression and data mining, is used to estimate and model the system components that can potentially fail during a predicted hurricane. The model is trained on artificial data and historical data from storm-related damages to predict component outages, where the prediction is further used in the proposed E-SCUC problem.

In addition, microgrids, as small-scale power systems with the ability of self-supply and islanding, are perceived as attractive investment options for both electrical system operators and end-use consumers due to the many economic, reliability, and energy efficiency benefits that they offer. One specific benefit of microgrids, which makes them extremely attractive, is the potential to improve resilience. The installation of microgrids in the proper places in power systems can be considered as a viable solution to power system resilience. Considering this issue and the growing number and intensity of extreme events, we developed a microgrid optimal placement model that determines the optimal size and location of microgrids in power systems to maximize system resilience. The model is developed considering multiple component outages and limited investment budget.

The rest of the chapter is organized as follow: Section 1.1 reviews the importance of power system resilience and introduces some of the existing work on improving power system resilience. Section 1.3 presents the literature on data driven approaches in system resilience and introduces the Kernel Density Estimation (KDE) method to estimate and model the system components that can potentially fail during a predicted hurricane. The importance of microgrids in power system resilience is presented in Section 1.3. Finally, an overview of the contributions in this thesis are presented in Section 1.4.

1.1. Power System Resilience

Extreme events, including severe weather events and natural disasters, result in significant economic, social, and physical disruptions, and cause considerable inconvenience for residents living in disaster areas due to loss of critical lifeline systems (Winkler et al. 2010). The electricity infrastructure has always been significantly impacted by extreme events as it is dispersed over a vast geographical area to transfer the electric energy generated by large-scale power plants to a variety of customers via transmission and distribution networks. The resulting power outages shut down businesses, impede emergency services, and cost the economy billions of dollars annually in lost output and wages, delayed production, inconvenience, and damage to the infrastructure (Executive Office of the President 2015). The topic of power grid resilience, i.e., the grid capability to withstand low-probability high-impact events by minimizing possible power outages and quickly returning to normal operating state (Karl 2009), has gained significant attention in recent years.

The importance of improving resilience in power systems is widely discussed in the literature; however, the mathematical modeling of optimal scheduling of available resources based on resilience considerations and efficient modeling of weather related incidents is limited. In (Ball 2006), a case study on hurricane planning and rebuilding the electrical infrastructure along the Gulf Coast for hurricane Katrina was presented. In (D. Reed et al. 2009), the interdependency of electricity and telecommunication infrastructures is considered during extreme events, and the resilience of networked infrastructures is analyzed. A resilience index for large infrastructures using belief functions is modeled in (Attoh-Okine et al. 2009) and a variety of qualitative explanations to address and analyze the system vulnerability is proposed. In (Arab, Khodaei, Han, et al. 2015), a framework for proactive recovery of electric power assets with the primary objective of resilience enhancement is introduced. The proposed framework develops outage models to indicate the impact of hurricanes on power system components, a stochastic pre-hurricane model for managing resources before the event, and a deterministic post-hurricane recovery model for managing resources after the event.

One important issue, which is typically overlooked in resilience studies, is the significant role of available generation units in ensuring a rapid and timely recovery of power system assets. This issue is discussed in (Arab et al. 2014) where impact of potential damage due to hurricanes is incorporated in the power system maintenance scheduling problem. The proposed model considers component deterioration, failure due to loss of reliability and hurricane damages, and the interrelationship between the components and the grid. The objective is to find a simultaneous cost-effective unit commitment (UC) and hurricane planning for preventive maintenance when the components fail due to degradation or hurricanes. It is concluded that the saving cost due to implementing the preventive maintenance program is significant and it is necessary to include resilience in UC.

1.2. Data Driven Approaches in System Resilience

In the context of data driven approaches to predict power system outages in response to hurricanes, the hurricane disruption in terms of number of outages and customers affected, geographic distribution and duration, causes of outages, and types of equipment affected, are studied in (Davidson et al. 2003). The study is based on large databases of outages in five hurricanes in Carolina. In (D. A. Reed 2008) data logs of the repair crews were plotted in GIS to study outage duration, fragilities, and restoration of an urban distribution system located in the U.S. Pacific Northwest that was affected by four winter storms. In (Nateghi, Guikema, and Quiring 2014), an ensemble learning method for regression (i.e. random decision forests) is proposed to forecast the power outage durations. The power outage duration models are developed and validated for outages caused by Hurricanes Dennis, Katrina, and Ivan in a central Gulf Coast state. In (Guikema et al. 2014), a hurricane power outage prediction model is introduced and claimed to be applicable along the full U.S. coastline. The model is trained on only publicly available data, and is further used to estimate the impacts of a number of historic storms, including Sandy and Typhoon Haiyan.

Considering the large number and the frequent occurrence of hurricanes in the U.S., which results in a considerable amount of data, machine learning methods could be of significant use. Kernel Density Estimation (KDE) method, as a non-parametric way to estimate the probability density function of a random variable, is used for this purpose (Parzen 1962). This method is commonly used in data mining, data smoothing, cluster analysis, image processing, signal processing, and econometrics (Guidoum 2013). In this case of study, KDE is used to analyze the historical hurricane and power system outage data and accordingly estimate the probability of failure for power system components in response to future events based on the center and the category of the hurricane

1.3. Microgrids

Microgrids, as small-scale power systems with the ability of self-supply and islanding, are perceived as attractive investment options for both electrical system operators and end-use consumers due to the many economic, reliability, and energy efficiency benefits that they offer. One specific benefit of microgrids, which makes them extremely attractive, is the potential to improve resilience. Power grid resilience represents the grid capability to withstand low-probability high-impact events by minimizing possible power outages and quickly returning to normal operating state (Executive Office of the President 2015). The topic of power grid resilience has received significant attention over the years as low-probability high-impact events, such as severe weather events and natural disasters, resulting in significant socioeconomic disruptions due to loss of critical infrastructure systems (Karl 2009). The power system is one of these critical infrastructures that has always been significantly impacted by extreme events, conceivably due to dispersion over vast geographical area to transfer the electric energy to consumers. The power outages caused by extreme events cost billions of dollars annually as a result of lost output, delayed production, and damage to the infrastructure (Executive Office of the President 2015). A study on rebuilding the power grid along the Gulf Coast, in response to hurricane Katrina, is presented in (Ball 2006). A new attack scenario is introduced in (Zhu et al. 2014), which considers a practical attack strategy based on attack graph to evaluate the power grid resilience. The interdependency of electricity and telecommunication infrastructures are considered during extreme events in (D. A. Reed, Kapur, and Christie 2009), where the resilience of networked infrastructures is further analyzed. A resilience index for large infrastructures using belief functions is modeled in (Attoh-Okine et al. 2009) and a variety of qualitative explanations to address and analyze the system vulnerability is proposed. The study in (Arab, Khodaei, Khator, et al. 2015) proposes a model for repair and restoration of potential damages to the power system based on a proactive resource allocation, which is modeled as a stochastic integer program and decomposed by the Benders decomposition to handle computation burden. A framework for proactive recovery of electric power assets is introduced in (Arab, Khodaei, Han, et al. 2015), seeking to enhance the grid resilience. Outage models are introduced, along with stochastic/deterministic models for managing resources in pre-/post-hurricane stages. The role of available generation units in ensuring the desired level of grid resilience is an important issue that is commonly ignored in these studies, but however, needs to be further taken into account. The significant role of generation units availability in ensuring a timely recovery is discussed in (Arab et al. 2014), where the likely damages due to extreme events is integrated with the maintenance scheduling problem. Component deterioration, failure due to extreme events, and the interdependency between the components and the grid are further considered in the proposed model, and accordingly, a simultaneous cost-effective unit commitment (UC) and hurricane planning for preventive maintenance was achieved. The study concluded that it is imperative to include resilience as part of the UC problem.

There are limited mathematical studies in the literature on the impact of microgrids on the power grid resilience. A comprehensive study of state-of-the-art methods of resilience in microgrids can be found in (Parhizi et al. 2015). The problem of integrating distributed generators (DG) to microgrids from an economic and reliable planning perspective is investigated in (Xu et al. 2014). A multi-objective optimization model which includes resilience by considering network capacity for self-recovery to a new normal state after an extreme event is introduced in (Cano-Andrade et al. 2012). A composite sustainability/resilience index is calculated using fuzzy logic which allows expression of sustainability and resilience indices in the same units. A resilience-oriented microgrid optimal scheduling model is proposed in (Khodaei 2014), which schedules available resources in case of utility grid supply interruption to minimize the microgrid load curtailments. The study in (Che and Shahidehpour 2014) suggests that by deploying microgrids in strategic locations, the power grid resilience can be enhanced.

In this model, the cost of lost loads, the repair cost, and the generation costs were considered as economic indices. The model suggested that investing on restoration resources can be paid off by securing expedited recovery. In resilience studies, ensuring adequate available generation plays an important role, which indicates the importance of unit commitment and economic dispatch studies. This issue is discussed in (Arab et al. 2014), where the impact of potential damage due to hurricanes is incorporated in the power system maintenance-scheduling problem. The proposed model considers component deterioration and also failure due to loss of reliability and failure due to hurricane damages. The objective is to find a simultaneous cost-effective unit commitment and hurricane planning for preventive maintenance when the components fail due to degradation or hurricanes. In the context of microgrid applications for power system resilience enhancement, limited work can be found in the literature, mainly focusing on the resilience improvement as a complimentary value proposition of microgrids. In (Xu et al. 2014), a case study of integrating distributed generators (DGs) to microgrids is investigated from a planning perspective which is modeled as an optimization problem with objectives of vulnerability, reliability, and economy. The optimization model is solved by a hybrid approach that combines multi-agent system and particle swarm optimization. However, the model is complicated and it is possible that the employed evolutionary method stops in a local minima. In (Cano-Andrade et al. 2012), a multi-objective resilience model is proposed in order to account for the capacity of the network to self-recover to a normal state after a natural disaster. The study in (Khodaei 2014) aims at minimizing the microgrid load curtailments by scheduling available resources when supply of power from the utility grid is interrupted. This study considers uncertainties in load, renewable generation, as well as the time and the duration of the electricity interruptions from the utility grid. This model is one of the few mathematical models of the microgrid optimal scheduling problem based on resilience considerations which uses a decomposition method to decouple the problem into two operational problems, i.e., normal and resilient. A comprehensive study of microgrids application in providing grid support is provided in (Parhizi et al. 2015).

1.4. Contributions

The contributions of this thesis are as follows:

1.4.1. Event-driven Security-Constrained Unit Commitment (E-SCUC)

An Event-driven Security-Constrained Unit Commitment (E-SCUC) model is proposed which considers the probabilistic damage model of the system components, develops proper scenarios to model the impact of forecasted extreme events on component outages, and determines the commitment and dispatch of available generation units to ensure an economic operation under normal conditions and a resilient operation under contingency cases. The focus on this study will be on hurricanes; however, the proposed models can be applied to other types of extreme events, without loss of generality, knowing the probability of arrival and damage on the system components. Unlike the current daily practice in system resource scheduling in which *N*-1 or *N*-2 reliability criteria are considered, the proposed E-SCUC allows for consideration of an extended number of outages, i.e., *N-1-m*, where *m* is determined in this study using probabilistic methods.

1.4.2. Component Outage Estimation Based on Statistical Learning

Since accurate estimation of the component outages is importance in planning and scheduling power systems especially during an extreme event, a Kernel Density Estimation (KDE) method is proposed and used to estimate component outages. As there are only a few publicly available datasets on the impact of the hurricanes on power system components, the proposed method is applied on artificial data to estimate the probability of components failures. The obtained component outages are further integrated to a developed E-SCUC model to find the optimal schedule of available resources that not only minimizes the operation cost but also lowers the system total load curtailment.

1.4.3. Role of Microgrids in Power System Resilience

In this study, an optimal microgrid placement model to enhance power system resilience is proposed. The size and location of microgrids are determined in order to minimize the load curtailments within the power system following hurricanes. The probabilistic failure model of the system components is considered to develop proper scenarios in order to model the impact of hurricanes on component outages. Moreover, this model characterizes a resilient operation under contingency cases. Microgrids are considered as aggregated and flexible loads from the system operator's perspective and their response to component outages are accordingly modeled. The proposed work follows the grid modernization plans of many electric utilities in the U.S., such as Commonwealth Edison in Chicago, to build microgrids in strategic places in order to address the negative impacts of extreme weather events and improve system resilience (Paaso, Svachula, and Bahramirad 2015), (Paaso, Liao, and Cramer 2015) .

2. CHAPTER TWO: POWER GRID MANAGEMENT

In this chapter, the model outline and formulation of the proposed approaches to enhance power system resilience are presented. Section 2.1 presents the proposed Event-driven Security-Constrained Unit Commitment (E-SCUC) problem and introduces two new proposed reliability criteria i.e. *N-m* and *N-1-m*. The formulation of the proposed E-SCUC is discussed in Section 2.1.1.

The proposed approach of component outage estimation based on the KDE is introduced in Section 2.2. Section 2.2.1 introduces Saffir-Simpson's category of hurricanes, and the formulation of the proposed Kernel Density Estimation (KDE) method to estimate component outages is discussed in Section 2.2.2.

Once the probable damages to system components are estimated, the buses in which microgrids are to be placed will be determined with the objective of minimizing the system total load curtailments. The role of microgrids in power system resilience and optimal microgrid placement formulation are presented in Section 2.3.

2.1. Event-driven Security-Constrained Unit Commitment (E-SCUC)

Figure 2-1 depicts the outline of the proposed E-SCUC model. The problem is solved in two consecutive stages. Stage 1 forecasts the path and the intensity of the hurricane that is headed toward the power system and accordingly identifies the potential regions that will be impacted by this event. Knowing the potential regions to be impacted and the power system components in that region, the outage probability of each component will be calculated. Using this probability, the set of components on outage in each region will be estimated. Once the probable damages to system components are estimated, Stage 2 solves the E-SCUC problem considering an *N-1-m* reliability criterion, in which *N* is the total number of components in the power system and *m* is the number of identified component outages in each region. In other words, the model simultaneously considers the power system security in response to the single component outage (*N-1*) and also in response to the outage of *m* components in impacted regions.

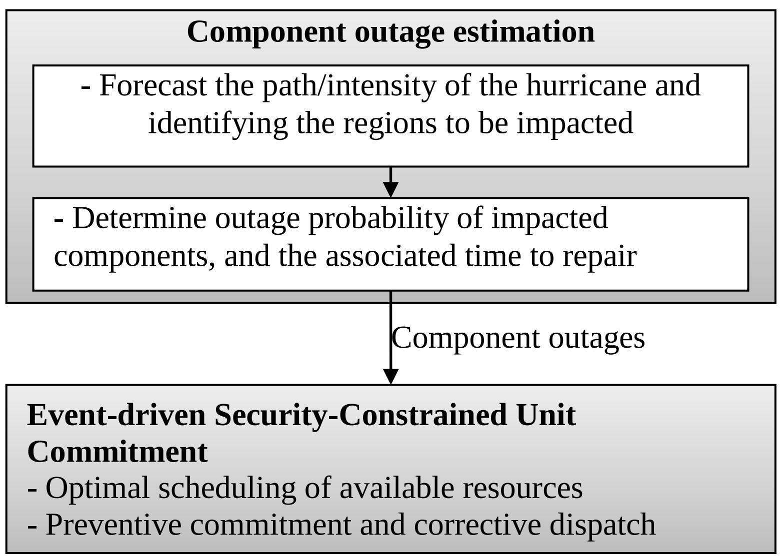

FIGURE 2-1- PROPOSED E-SCUC MODEL

The component state is considered as a random variable, representing two states of outage and operational. Variety of probability distribution models have been proposed to model weather-related outage rate and probability of damage of power system components (Arab et al. 2014; Abiri-Jahromi et al. 2013). For example, the Poisson distribution is used to model the hurricane arrival rate in (Lu and Garrido 2005) and (Arab et al. 2014). Also, along with hurricane arrival rate, the maximum wind gust speed that the component is able to withstand needs to be considered to evaluate the probability of outage. Hurricanes in general exhibit spatial and temporal dependence structures. Spatial dependence refers to the fact that locations within some distance from the path of the event will encounter rather similar impact patterns, and temporal dependence refers to the consecutive periods that will encounter similar behavior from the event until it is passed. Various methods have been studied for the statistical modeling of extreme events in space and time using max-stable model with deterministic storm shapes (Smith 1990), pairwise censored likelihood (Huser and Davison 2014), and spatial intensity function of the background occurrences for earthquakes (Zhuang, Ogata, and Vere-Jones 2002). This study relies on the existing literature to determine the shape of the hurricane, and accordingly, focuses on the components' probability of outage. It is assumed that the components in center of the hurricane have higher probability of outage with lower probability of outage in neighboring locations. The impacted region may contain generation units, transmission lines, substations, and load sites. Therefore, it is possible that more than one component are on outage due to the hurricane.

It is common to use the N-1 criterion for reliability studies in power systems, where N in the total number of components in the system. This criterion expresses that the network should be designed such that all the loads are seamlessly supplied in case of a single component outage at any given time. Following a hurricane, more than one component can be out of service; accordingly, the N-1 criterion cannot guarantee the desired operation. To address this issue, this study employs an extended criterion, i.e., *N*-*m*, to consider the simultaneous outage of *m* components. The *N*-*m* criterion ensures that the system is resilient against any *m* component outages from the set of components within the impacted area. It should be noted that if *m* components are impacted, there will be 2^m possible failure scenarios. Since it is not practical to consider all possible scenarios, only scenarios with higher probability are studied. To do this, first the outage probability of potentially impacted power system components is determined, followed by calculating the occurrence probability of each scenario. Scenarios with higher occurrence probability are considered as the representatives of the entire outage scenarios. In addition to the proposed *N*-*m* criterion, the *N*-1-*m* criterion is also proposed and used in this study, which ensures that the system satisfies the *N*-1 reliability criterion for the entire system while it is also resilient against any *m* component outages from the set of components within the impacted area by the hurricane. For example, assuming we have 47 components in the system, and three scenarios for *N*-*m* criterion (top three scenarios with higher occurrence probability), in *N*-1-*m* criterion 50 scenarios are defined in the system, where 47 scenarios representing the single component outage (*N-1*) and three representing outage scenarios for each path of the hurricane (*N-1-m*).

Moreover, when a component is damaged by the hurricane, a certain amount of time is required to repair the component (known as time to repair or TTR). In (Nateghi, Guikema, and Quiring 2011), it was shown that the time to repair is a function of the number of crews, geographic characteristics of the area such as land use and land cover data, and climatic variables such as event duration and intensity. The time to repair of each component can be seen as a random variable, due to variation in skill level of the repair crew and the random nature of the degree of damage (Arab, Khodaei, Han, et al. 2015). This issue is further considered in this study.

2.1.1. E-SCUC Formulation

2.1.1.a) Outage Estimation

The intensity and the path of hurricane can be obtained from weather forecast agencies. Component damages, however, are modeled using probabilistic models. The more accurate model to forecast the component damages based on the intensity and path of the hurricane, the more reliable system can be scheduled and operated. Unfortunately, there are not many data available for the impact of previous hurricanes on the system components (perceivably due to the priority in restoring the system and recovering the supply of power over event recording) and many utilities have trouble assembling this data even internally. Instead, stochastic modeling can be used to predict the probability of an outage of each component, assuming a certain probability model for each hurricane and the probability of the withstanding against wind gust speeds.

In this study, two major components are identified for damage modeling including generation units and transmission lines. Damage state can be considered as a random variable with two outcomes: damaged and operational. Therefore, a Bernoulli random variable can be adopted to model the damaged/operational state of each component. The Bernoulli random variable, takes the value of 1 when the state of the component (*UX* and *UY*) is considered operational (with probability *p*); and takes the value of 0, when the component is considered to be in damaged state (with probability 1-p). The availability function of each component against hurricane is considered as a dynamic stress-strength model as defined below:

$$R(\tau)=\sum_{m}^{\infty}P\{G_1<G_1',G_2<G_2',\ldots,G_{N(\tau)}<G_{N(\tau)}'|N(\tau)=m\}P(N(\tau)=m) \qquad (1)$$

where $R(\tau)$ is the reliability function, $N(\tau)$ is the number of hurricane strikes, τ is the time window of upcoming hurricane, and G_i is the outcome of the i^{th} random wind shock from the wind gust speed random variable G. In this study, the arrival probability of the hurricane during each operating period is modeled by Poisson distribution (Russell, Schueller, and others 1974), while the survival of component against wind gust is modeled by Lognormal distribution (Winkler et al. 2010). For the sake of simplicity, deterioration level of the component is not considered in the probability of outage in this study. However, the formulation is a general framework that can be expanded to other probability distributions. In addition, the time to repair damaged components is defined by the Weibull density function (2)

$$f(t)=\begin{cases}\dfrac{\rho}{\lambda}\left(\dfrac{t}{\lambda}\right)^{\rho-1}e^{-(t/\lambda)^{\rho}} & \text{if } t\geq 0\\ 0 & \text{otherwise}\end{cases} \qquad (2)$$

where ρ is the shape parameter, and λ is the scale parameter. Which can be replaced by other probability distributions, such as Exponential, Gamma, and Normal, without loss of generality (Billinton and Wang 1999): Each component has different repair time and required set of skilled crews in practice. In this study, without loss of generality, a same shape parameter and scale parameter is considered for different unit types, and the expected value of the time to repair random variable used as a reliable substitute for time to repair.

2.1.1.b) E-SCUC

The objective of the E-SCUC problem is defined as:

$$\min \sum_{t}\sum_{i} F\left(P_{it0}, I_{it}\right) + \sum_{t}\sum_{s}\sum_{b} vLC_{bts} \tag{3}$$

where $F(P_{it0}, I_{it})$ is the operation cost in normal system operation (which includes the generation cost and startup/shut down costs) and LC_{bts} is the cost of unserved energy at bus b at time t during contingency scenarios s. The value of lost load, v, is defined as the average cost that each type of customer - residential, commercial, or industrial - is willing to pay in order to avoid load interruptions (Economics 2013). Assuming UX_{its} as the outage state of unit i at time t in scenario s (1 when operating and 0 when on outage) and UY_{lts} as the outage state of line l at time t in scenario s (1 when operating and 0 when on outage), the proposed objective function is subject to the following operational constraints:

$$\sum_{i\in B} P_{its} + \sum_{i\in B} PL_{its} + LC_{bts} = D_{bt} \qquad \forall b, \forall s, \forall t \tag{4}$$

$$P_i^{\min} I_{it} UX_{its} \le P_{its} \le P_i^{\max} I_{it} UX_{its} \qquad \forall i, \forall s, \forall t \tag{5}$$

$$P_{its} - P_{i(t-1)s} \le UR_i \qquad \forall i, \forall s, \forall t \tag{6}$$

$$P_{i(t-1)s} - P_{its} \le DR_i \qquad \forall i, \forall s, \forall t \tag{7}$$

$$T_{it}^{\text{on}} \ge UT_i\left(I_{it} - I_{i(t-1)}\right) \qquad \forall i, \forall t \tag{8}$$

$$T_{it}^{\text{off}} \geq DT_i\left(I_{i(t-1)} - I_{it}\right) \qquad \forall i, \forall t \qquad (9)$$

$$\sum_i P_i^{\max} I_{it} \geq D_t + R_t \qquad \forall i, \forall t \qquad (10)$$

$$\left|P_{it0} - P_{its}\right| \in \Delta_i \qquad \forall i, \forall s, \forall t \qquad (11)$$

$$PL_l^{\min} UY_{lts} \leq PL_{lts} \leq PL_l^{\max} UX_{lts} \qquad \forall l, \forall s, \forall t \qquad (12)$$

$$\left|PL_{lts} - \frac{\sum_b a_{lb}\theta_{bts}}{x_l}\right| \leq M\left(1 - UY_{lts}\right) \qquad \forall l, \forall s, \forall t \qquad (13)$$

Load balance equation (4) ensures that the total injected power to each bus from generation units and line flows is equal to the total consumed load at each load bus. Load curtailment variable (LC_{bts}) is further added to the load balance equation to ensure a feasible solution when there is not sufficient generation to supply loads (due to outage of power system components). Load curtailment will be zero under normal operation conditions. Generation unit output power is limited by its capacity limit and will be set to zero depending on its commitment and outage states (5). Generation units are further subject to prevailing technical constraints including ramp up and down rate limits (6)-(7), minimum up and down time limits (8)-(9). System operating reserve requirement is represented in (10). The change in unit generation is further limited by the maximum permissible limit between normal and contingency scenarios (11). Transmission line capacity limits and power flow constraints are modeled by (12) and (13), respectively, in which the outage state is included to effectively model the line outages in contingency scenarios.

The proposed model ensures that the obtained unit schedule provides a cost-effective solution in normal system operation and a secure solution in case of multiple component outages. Component outages are handled by a combination of proper preventive actions (i.e., commitment of additional generation units) as well as corrective actions (i.e., generation redispatch of committed units). The outcome of this model is an event-driven SCUC model that can be utilized when an extreme event is forecasted to approach the system, thus assuring that the system is ready to face the event and the probable load curtailments in response to multiple component outages will be reduced.

2.2. Component Outage Estimation Based on KDE

Figure 2-2 depicts the outline of the proposed E-SCUC model. The model has three stages. In Stage-1, the category and the path of the potential hurricane that is heading toward the power system is forecasted. This forecast data can be obtained from weather forecast channels. In Stage-2, after knowing the potential regions and the category of the hurricane, the outage probability of each system component is calculated using KDE method on historical hurricane data. As the publicly available data on the impact of hurricanes on power system components is limited, an artificial set of data is generated in this study to estimate the probability of the component outages. Once the probable damages to system components are estimated, the E-SCUC problem based on the obtained scenarios of outages is solved in Stage-3.

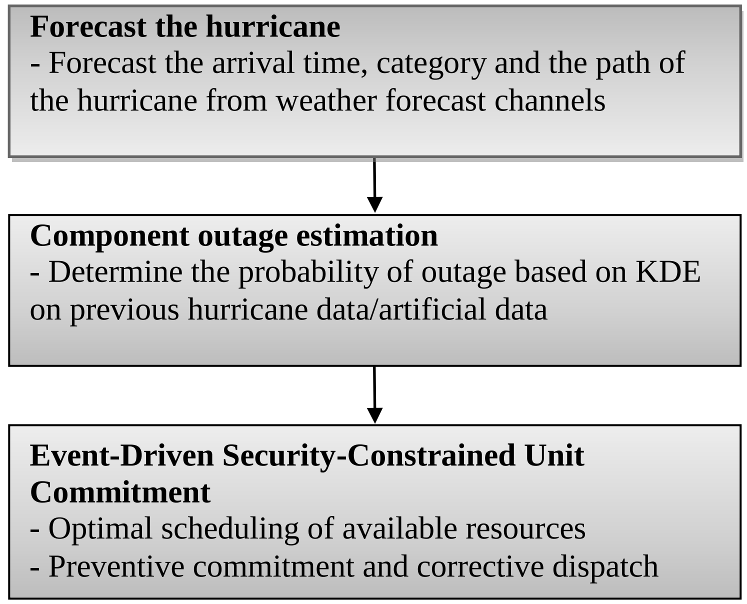

FIGURE 2-2- PROPOSED E-SCUC MODEL WITH MACHINE LEARNING-BASED OUTAGE ESTIMATION

2.2.1. Categories of Hurricanes

A hurricane is typically assigned a "*category*" of one through five based on its maximum 1-minute sustained wind speed according to the Saffir-Simpson Hurricane Scale (Schott et al. 2012). The minimum and maximum sustained wind speeds corresponding to each hurricane category are shown in Table 2-1. Category 1 and 2 storms, with sustained winds of 74-95 mph and 96-110 mph, respectively, are less dangerous categories but however require preventive measures. Usually there is no significant structural damage to most well-constructed permanent structures or there are only minor damages to poorly constructed windows or doors. However extensive power outages may happen lasting from few minutes to several days. The U.S. National Hurricane Center classifies hurricanes of Category 3 and above as major hurricanes.

Category 3 hurricanes can cause some structural damage to small residences and utility buildings, particularly those of wood frame. There is a very high risk of injury or death in Category 4, and catastrophic damage will occur in hurricane Category 5 (Schott et al. 2012). Since the extreme wind rating of utility structures is based on a three-second gust, it is also useful to think of hurricane categories in terms of gust speeds. A typical hurricane will have three-second gusts that are about 25% greater than one-minute sustained wind speeds (Brown 2009). Using this 25% gust factor, the minimum and maximum expected three-second gust speeds corresponding to each hurricane category are shown in Table 2-1.

TABLE 2-1- SAFFIR-SIMPSON HURRICANE SCALE

	1-min sustained (mph)		3-sec gust (mph)	
Category	Min	Max	Min	Max
1	74	95	93	119
2	96	110	120	138
3	111	130	139	163
4	131	155	164	196
5	156	180	195	225

2.2.2. Kernel Density Estimation (KDE)

The operational/outage state of a component can be considered as a random binary variable. A variety of probability distribution models have been proposed to model the probability of damages on the power system components (Arab et al. 2014; Abiri-Jahromi et al. 2013). Given a sample $x \in \mathbb{R}^d$ from some unknown densities, the general form of a multivariate kernel density estimate at *x* is computed as

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{14}$$

where K is d-variate function (the kernel), x_i is the training example, n is the number of training examples and h is a smoothing parameter called the *bandwidth*. The bandwidth is a rescaling factor, which determines the extent of the region over which the probability mass for a point x_i is spread. The kernel is generally chosen to be an even function, i.e., $K(x) = K(-x)$, which usually integrates to one and has a mean value of zero. The most widely used kernel is the Gaussian of zero mean and unit variance as:

$$K(x) = \frac{1}{\sqrt{(2p)^d}} \exp\left\{ - \frac{\|x\|}{2} \right\} \qquad (15)$$

KDE methods are not very sensitive to the choice of K, and different functions that produce good results can be used. In practice, the bandwidth plays an important role and has a great effect on the shape of the estimator. If the bandwidth is small, an under-smoothed estimator with high variability will be obtained. On the contrary, a large bandwidth results in an over-smooth estimator and farther from the estimated function. Thus, the quality of a kernel density estimator highly depends on the choice of the smoothing parameter. A common way to estimate an optimum value of the bandwidth is by measuring the mean integrated squared error (MISE) between the density and its estimate integrated over the domain of definition (across the training examples) as in (16) (Wand and Jones 1994):

$$MISE(h) = \int_{\Re^d} \left(\hat{f}_h(x) - f(x) \right)^2 dx \qquad (16)$$

In other word, a KDE with different bandwidth is applied on training examples and the bandwidth with minimum MISE is assumed as the optimal bandwidth. Figure 2-3 illustrates the effect of bandwidth on KDE of a standard normal distribution. As shown, small bandwidth (h=2) results a higher variability estimation and a large bandwidth (h=20) results in an over-smooth estimator, while the calculated optimal bandwidth can estimate the probability of random samples more accurately.

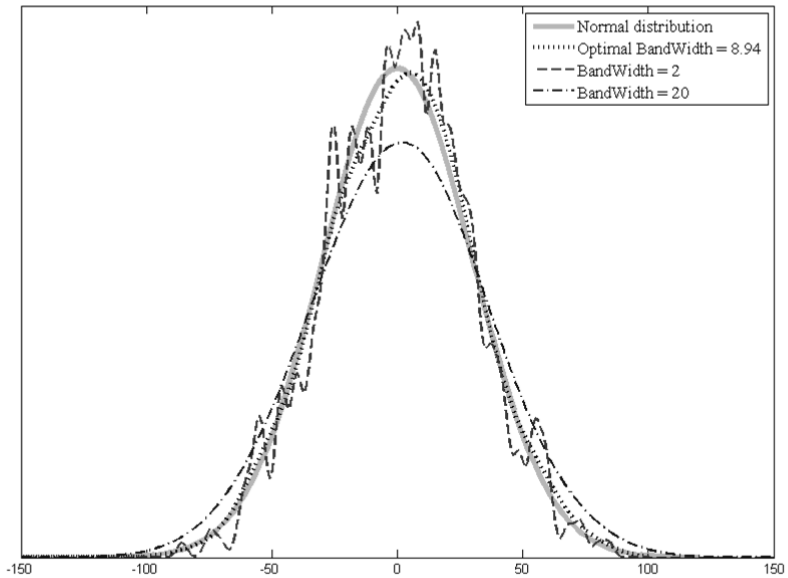

FIGURE 2-3- KERNEL DENSITY ESTIMATION (KDE) WITH DIFFERENT BANDWIDTH TO ESTIMATE A STANDARD NORMAL DISTRIBUTION

2.3. Role of Microgrids in Power System Resilience

The path and the intensity of the upcoming hurricane, which can be obtained from weather forecasting channels, will be collected as a first step. Then, according to the potential regions to be impacted by the hurricane, the outage probability of the components in those regions will be calculated. Once the probable damages to system components are estimated, the buses in which microgrids are to be placed will be determined with the objective of minimizing the system total load curtailments.

Component outages should be modeled by probabilistic distribution functions using the hurricanes' intensity and path that are obtained from weather forecasting agencies. Since there are not many data available for the impact of previous hurricanes on the system components, stochastic modeling can be used to predict the probability of component outages, which assumes a certain probability model for each hurricane. The components can have two states of damaged (i.e., on outage) and operational (i.e., in service). A variety of distribution models have been proposed to model weather related failure rate and probability of failure/damage of power system components (Arab et al. 2014) (Abiri-Jahromi et al. 2013). In (Arab et al. 2014), the deterioration levels of the components have also been taken into account to calculate the probability of failure, where the higher the level of deterioration, the higher the probability of failure. In this study, the arrival probability of hurricanes during each operating period is modeled by Poisson distribution (Russell, Schueller, and others 1974), while the survival of components against wind gust is modeled by Lognormal distribution (Winkler et al. 2010). For the sake of simplicity, the deterioration level of the components is not considered in this study. However, the formulation is general and can be expanded to other probability distributions based on the extreme weather event and components characteristics. By nature, extreme events exhibit a spatial dependence structure, meaning that neighboring locations within some distance show similar patterns, as well as temporal dependence, which can be seen from similar high values for two consecutive time periods (e.g. within hours). Each type of extreme event has different spatial dependency and pattern, as studied in this study. The components impacted by a hurricane may contain generation units and transmission lines. The objective of this study is to find the optimal size and location of microgrids in order to minimize load curtailments in the entire system and to ensure a resilient operation. During normal operation, i.e., without any component outages, the loads are fully supplied by the generation units. In the event of component outages, however, loads in buses located in the impacted area will be partially supplied by microgrids. Two sets of binary parameters are employed to consider the failure state: UX_{its} as the failure state of unit i at time t in scenario s and UY_{lts} as the failure state of line l at time t in scenario s (in both cases, 1 when operating and 0 when on outage). Since binary parameters can have only two states, Bernoulli random variable can be adopted to model the operational state (with probability p) and damaged state (with probability 1-p) for each component.

2.3.1. Optimal Microgrid Placement Formulation

The optimal microgrid placement model to ensure the system resilience against hurricanes is formulated as follows:

$$\min \sum_t \sum_s \sum_b v_b LC_{bts} \tag{17}$$

$$\sum_{i \in B} P_{its} + P_{bts}^M + \sum_{l \in B} PL_{lts} + LC_{bts} = D_{bt} \qquad \forall b, \forall s, \forall t \tag{18}$$

$$0 \le P_{its} \le P_i^{\max} I_{it} UX_{its} \qquad \forall i, \forall s, \forall t \tag{19}$$

$$\left| P_{its} - P_{it0} \right| \le \Delta \qquad \forall i, \forall s, \forall t \tag{20}$$

$$\left| PL_{lts} \right| \le PL_l^{\max} UY_{lts} \qquad \forall l, \forall s, \forall t \tag{21}$$

$$\left| PL_{lts} - \left(\sum_b a_{lb} \theta_{bts} \right) / x_l \right| \le M(1 - UY_{lts}) \qquad \forall l, \forall s, \forall t \tag{22}$$

$$0 \le P_{bts}^M \le P_b^{M,\max} \qquad \forall b, \forall s, \forall t \tag{23}$$

$$P_b^{M,\max} \le kD_b^{\max} \qquad \forall b \qquad (24)$$

$$0 \le LC_{bts} \le (1-k)D_{bt} \qquad \forall b, \forall s, \forall t \qquad (25)$$

$$\sum_b CC_b P_b^{M,\max} \le Budget \qquad (26)$$

$$u_{bts} = \prod_l |a_{lb}| UY_{lts} \qquad \forall b, \forall s, \forall t \qquad (27)$$

$$P_{bts}^M \le kD_{bt}(1-u_{bts}) \qquad \forall b, \forall s, \forall t \qquad (28)$$

The objective function (17) is the cost of unserved energy during outage scenarios. The cost of unserved energy is the value of lost load (VOLL) times the amount of load curtailments in each scenario. VOLL represents customers' willingness to pay for reliable electricity service in order to avoid interruptions, and is different for different customer types, i.e., residential, industrial, and commercial (Lotfi and Khodaei 2015). In this problem, it is assumed that the loads are supplied by the utility grid, and its operation is separate from microgrids' operation, so the system operation cost is not considered in the objective function. Instead, there is a limited budget to increase the system resilience by installing microgrids with optimal size and location. This assumption is in line with practice for many electric utilities under deregulated environments that can use microgrids for reliability and resilience improvement but not for economic purposes. The constraints associated with the objective function (17) are defined in (18)-(28). The load balance equation (18) ensures that the sum of total power generated by generation units and the microgrid as well as line flow injections at each bus is equal to the bus load during all scenarios. The load curtailments variable LC_{bts} will be zero under normal conditions. The power output of generation units is limited by their capacity limits and can be set to zero depending on their commitment state and the failure state (19). The minimum generation capacity is considered to be zero to remove the need for accurately modeling commitment states in each operation time period. The change in the power of generation units between normal and contingency operations is limited by the maximum permissible change (20). The line flow is limited by the line capacity and outage state in contingency scenarios (21)-(22). If a transmission line is on outage, i.e., $UY_{lts}=0$, its power flow would be zero and that line will be removed from the power flow equations. The microgrid generation at each bus in all times and scenarios is limited by its installed capacity (23). The microgrid installed capacity at each bus is assumed to be limited by a predetermined ratio of the maximum load at that bus (24). In other words, a maximum of kD_b^{max} can be supplied by the microgrid where D_b^{max} is the peak load at bus b. The amount of load curtailments at each bus in each scenario is limited by the amount of load not supplied by the microgrid at that bus (25). By changing the microgrid capacity, the load curtailments can be potentially reduced (Khodaei 2014) (Shahidehpour 2010). Furthermore, the sum of the investment cost of all installed microgrids in the system cannot exceed the available budget set by the system planner (26).

Based on the definition, the microgrid is switched to the islanded mode in response to upstream network disturbances. Considering this, if any of the lines connected to the microgrids upstream bus is on outage due to the hurricane, the microgrid will be disconnected from the system. The microgrid operation state is defined as the product of failure state of lines connecting to the microgrid bus (27). If any of these lines is on outage, the microgrid operation state u_{bts} would be set to zero, i.e., the microgrid is in the islanded mode, otherwise grid-connected. The proposed constraint is linearized to ensure the MIP nature of the developed formulation as in (29).

$$\frac{\sum_l |a_{lb}| UY_{lts}}{\sum_l |a_{lb}|} - 1 + \varepsilon \le u_{bts} \le \frac{\sum_l |a_{lb}| UY_{lts}}{\sum_l |a_{lb}|} \qquad \forall b, \forall s, \forall t \qquad (29)$$

When switched to the islanded mode, the microgrid load from the system operator's perspective will be zero, meaning that the microgrid will supply its forecasted load, i.e., kD_{bt}, thus the maximum microgrid load can be modeled as in (28). The proposed formulation efficiently models the microgrid grid-connected and islanded operation modes, while ensuring a reliable operation of the entire system in case of upstream network outages caused by hurricanes.

3. CHAPTER THREE: NUMERICAL SIMULATIONS

This chapter presents the numerical simulations of the proposed approaches for enhancing system resilience. The proposed E-SCUC problem is applied to the standard IEEE 30-bus test system in Section 3.1. In order to exhibit the effectiveness of the proposed model, three cases are studied as: Case 1) SCUC with *N-1* reliability, Case 2) SCUC with *N-1* reliability against m outages, and Case 3) E-SCUC with *N-1-m* reliability. The obtained results advocate that by increasing the number of simultaneous component outages, the operation cost increases, evidently due to the increased number of units that need to be committed in the normal operation and used in contingencies.

Section 3.2 presents the numerical simulation of the proposed component outage estimation based on the machine learning method and the E-SCUC problem on the IEEE 30-bus test system. The proposed KDE approach is trained on artificial data and used to estimate component outage. The outage scenarios are then used to evaluate the proposed E-SCUC in improving system resilience comparing with SCUC in three different case studies: Case 1) SCUC with *N-1* reliability, Case 2) SCUC with *N-1* reliability against *m* outages, and Case 3) Proposed E-SCUC comparing with SCUC. Comparing the results of E-SCUC with SCUC indicates that the proposed E-SCUC model is more resilient against multiple simultaneous component outages.

The optimal microgrid placement model ensures the system's resilience is applied to the standard IEEE 30-bus in Section 3.3. Four cases are studied:

- Case 1: Load curtailments calculation without microgrid installations
- Case 2: Load curtailments calculation with microgrid installations
- Case 3: Impact of the investment budget on system load curtailments
- Case 4: Impact of the ratio of loads supplied by microgrids on system load curtailments

The results demonstrate the importance of micogrids in power system resilience and show that increasing the ratio of the loads supplied by microgrids would significantly reduce the total load curtailments due to the capability of installing larger microgrid capacities.

3.1. Event-driven Security-Constrained Unit Commitment (E-SCUC)

The proposed E-SCUC problem is applied to the standard IEEE 30-bus test system as shown in Figure 3-1 ("IEEE 30-Bus System - Illinois Center for a Smarter Electric Grid (ICSEG)," n.d.). A hurricane passes through three hypothetical paths with different intensities. The procedure introduced in (Arab et al. 2014) is followed to find the probability of survival for each system component in response to a forecasted hurricane. Particularly, based on the available hurricane data and maximum wind gust speed that the components can withstand (Lu and Garrido 2005), the probability of survival from each hurricane is found. The impacted regions are also shown in Figure 3-1. Table 3-1 shows the components that are damaged in the path of hurricanes in three contingency scenarios (hurricane paths).

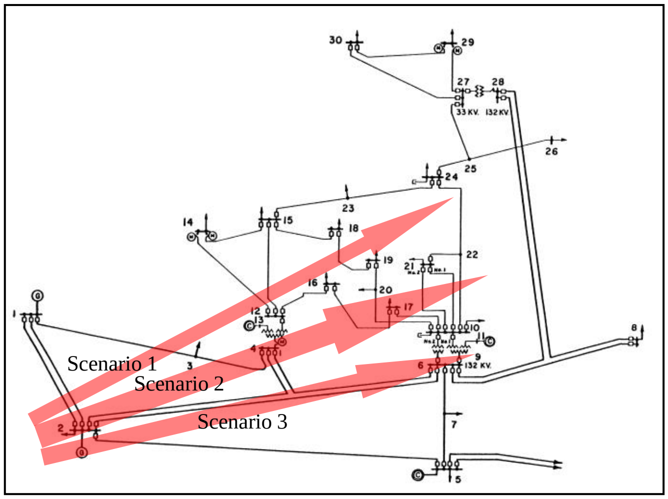

FIGURE 3-1- IEEE 30-BUS TEST SYSTEM AND THE FORECASTED HURRICANE PASSING THROUGH THREE HYPOTHETICAL PATHS IN THE SYSTEM

TABLE 3-1- SIMULTANEOUS COMPONENTS ON OUTAGE ALONG HURRICANE PATH (L: TRANSMISSION LINE, G: GENERATION UNIT)

	Scenario 1	Scenario 2	Scenario 2
m=1	L1	L3	G1
m=2	L1, L2	L3, L2	G1, L3
m=3	L1, L2, L17	L3, L2, L4	G1, L3, L4
m=4	L1, L2, L17, L20	L3, L2, L4, L1	G1, L3, L4, L16
m=5	L1, L2, L17, L20, L18	L3, L2, L4, L1, L16	G1, L3, L4, L16, L17
m=6	L1, L2, L17, L20, L18, L30	L3, L2, L4, L1, L16, L18	G1, L3, L4, L16, L17, L6
m=7	L1, L2, L17, L20, L18, L30, L32	L3, L2, L4, L1, L16, L18, L17	G1, L3, L4, L16, L17, L6, L5
m=8	L1, L2, L17, L20, L18, L30, L32, L22	L3, L2, L4, L1, L16, L18, L17, L20	G 1, L3, L4, L16, L17, L6, L5, L9

In order to exhibit the effectiveness of the proposed model, three cases are studied as follows:

3.1.1. SCUC with *N-1* reliability

In this case, only one component outage is considered in each contingency scenario, i.e., an *N*-1 reliability criterion is imposed. The operation cost is obtained as

$10,730. No load curtailment has occurred in this case, so the cost of unserved energy is zero and the system is secure against any single component outage.

3.1.2. SCUC with *N-1* reliability against m outages

In this case, the calculated commitment in Case 1 is used to solve the problem for the *m* component outages along hurricane path in each contingency scenario. The purpose of this study is to identify how much load curtailment will occur if the system is scheduled for *N*-1 but is subject to an extreme event. Table 3-2 shows the system operation cost and the load curtailment (LC) of each contingency scenario obtained from solving the SCUC problem based on the identified outages. As the same commitment is used for each number of component on outage (m), the total operation cost is constant. However, the results indicate that by increasing the number of simultaneous component outages, the load curtailment increases drastically. In other words, although the *N*-1 criterion is suitable for ensuring power system security in daily operation, but it is not a viable criterion when dealing with extreme events.

TABLE 3-2- OPERATION COST AND LOAD CURTAILMENT OF SCUC FOR MULTIPLE COMPONENT OUTAGES

	Total Cost	LC Scenario 1 (MWh)	LC Scenario 2 (MWh)	LC Scenario 3 (MWh)
m=1	$10,730	0	0	0
m=2	$10,730	180	0	0
m=3	$10,730	180	33	146
m=4	$10,730	180	180	146
m=5	$10,730	180	180	348
m=6	$10,730	180	184	348
m=7	$10,730	315	373	834
m=8	$10,730	318	373	862

3.1.3. E-SCUC with *N-1-m* reliability

In this case, the proposed E-SCUC is used to consider the simultaneous outage of *m* components along with the *N*-1 reliability criterion. Particularly, 50 scenarios is defined in the system, 47 scenarios representing the single component outage (*N*-1) and 3 representing outage scenarios for each path of the hurricane (*N-1-m*). Table 3-3 shows the system operation cost and the load curtailment of each contingency scenario obtained from solving the E-SCUC problem based on the identified outages. In addition, the cost increase and average load curtailment decrease compared to the SCUC with *N-m* reliability criterion (Case 2) are shown in Table 3-3.

TABLE 3-3- OPERATION COST AND LOAD CURTAILMENT OF THE PROPOSED E-SCUC FOR STUDIED SCENARIOS

	Total Cost	Cost Increase	LC S1 (MWh)	LC S2 (MWh)	LC S3 (MWh)	Avg. LC Decrease
m=1	$10,759	0.27%	0	0	0	0%
m=2	$10,865	1.24%	70	0	0	61%
m=3	$10,874	1.33%	70	33.70	67	55%
m=4	$10,890	1.48%	112.77	80	67	49%
m=5	$11,259	4.71%	117.05	88	131	52%
m=6	$11,259	4.71%	118.94	88	131	52%
m=7	$11,315	5.17%	215.05	130	316	57%
m=8	$11,320	5.21%	234.92	175	464	44%

The obtained results advocate that by increasing the number of simultaneous component outages, the operation cost increases, evidently due to the increased number of units that need to be committed in the normal operation and used in contingencies. Comparing the results of E-SCUC with SCUC (Case 2) indicates that the proposed E-SCUC model is more resilient against multiple simultaneous component outages as the amount of load curtailment is considerably lower than SCUC problem in same contingency scenarios. This significant advantage is obtained at the expense of limited cost increase, which is less than 6% in all studied cases. The final decision on the number of outages, i.e., *m*, represents a tradeoff between solution cost and resilience that need to be made by the system operator.

3.2. Component Outage Estimation Based on KDE

The proposed component outage estimation based on KDE and E-SCUC problem is applied to the IEEE 30-bus test system. It is assumed that a hurricane passes through three hypothetical paths with different categories as shown in Figure 3-1 ("IEEE 30-Bus System - Illinois Center for a Smarter Electric Grid (ICSEG)," n.d.). Five hundred samples with different wind gust speeds around the center of the hurricane are generated following a normal distribution with a small noise (10%). Accordingly, a Gaussian kernel is applied on the center of the hurricane to estimate the probability of failure of each component. Figure 3-2 shows the estimated probability of component failure for each hurricane category. The optimal bandwidth is estimated as 4.86 (Category 1 & 2), 9.76 (Category 3), 16.22 (Category 4), and 26.75 (Category 5). The proposed probability distribution functions can be better estimated if more significant and reliable data from previous hurricanes were available; however, the proposed model is a general framework that can be applied to any available set of data, with different degrees of accuracy, without loss of generality. In each hurricane path, based on the distance of each component to the center of the hurricane and the category of the hurricane, the probability of survival is determined. Table 3-4, Table 3-5, and Table 3-6 show the probability of failure for different components in each studied area (shown in Figure 3-1) based on data mining and KDE on artificial data. Probability of component failure over a threshold of 0.1 is considered for component failure (shown bold in Table 3-4, Table 3-5, and Table 3-6).

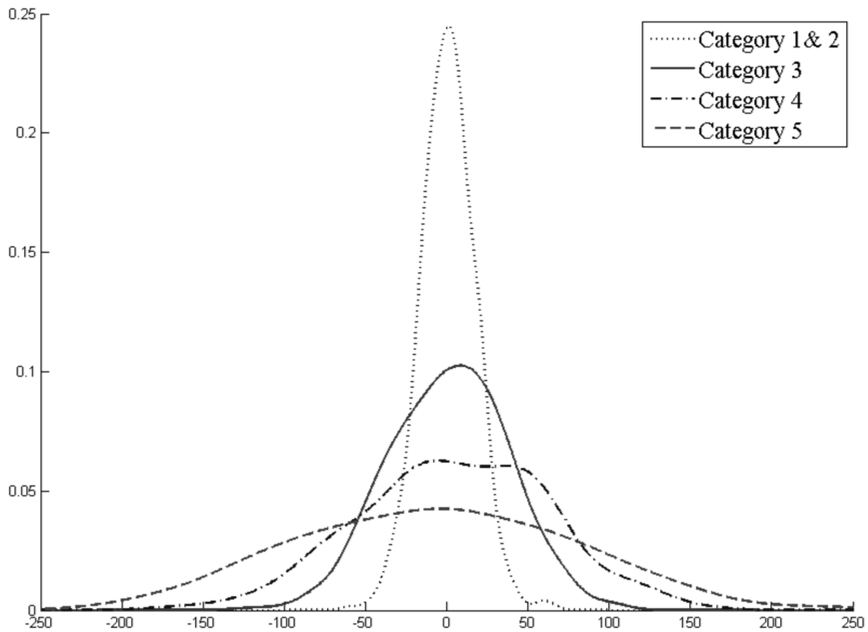

FIGURE 3-2- ESTIMATED PROBABILITY DENSITY FUNCTION OF COMPONENT FAILURE FOR EACH HURRICANE CATEGORY

3.2.1. SCUC with *N-1* Reliability

In this case, *N*-1 reliability criterion is considered in each contingency scenario. The operation cost is obtained as $10,730. No load curtailment has occurred in this case, and the system is secure against any single component outage.

3.2.2. SCUC with *N-1* Reliability against m Outages

The purpose of this case study is to identify how much load curtailment will occur if the system is scheduled for *N*-1 but multiple components outage happen due to an extreme event. In other words, the calculated commitment in Case 1 is used to solve the problem for the *m* component outages in each contingency scenario. Component outages along each hurricane path (contingency scenario) are shown bold in Table 3-4, Table 3-5, and Table 3-6. A cut-off probability of 0.1 is considered, i.e., any failure probability larger than this will result in component outage, while probabilities less than this will ensure that the component will continue to operate in the functional state.

TABLE 3-4- PROBABILITY OF FAILURE FOR DIFFERENT COMPONENTS IN HURRICANE PATH 1.

	Category			
	1 & 2	3	4	5
Line 5	**0.3882**	**0.4031**	**0.3646**	**0.3424**
Line 6	0.0393	**0.2623**	**0.3274**	**0.3077**
Line 7	0.0099	**0.2069**	**0.3067**	**0.2892**
Line 25	0.0045	**0.1345**	**0.2722**	**0.2687**
Line 26	0	0.0264	**0.1447**	**0.2091**
Line 27	0	0.0198	**0.1188**	**0.1924**
Line 28	0	0.0006	0.0632	**0.134**
Line 31	0	0.0004	0.0598	**0.1309**

TABLE 3-5- PROBABILITY OF FAILURE FOR DIFFERENT COMPONENTS IN HURRICANE PATH 2.

	Category			
	1 & 2	3	4	5
Line 5	**0.3397**	**0.4383**	**0.3802**	**0.3601**
Line 6	0.0676	**0.292**	**0.3153**	**0.3083**
Line 7	0.0104	**0.1781**	**0.2775**	**0.2816**
Line 21	0.0001	0.0775	**0.2202**	**0.2483**
Line 23	0	0.0661	**0.2088**	**0.2435**
Line 24	0	0.0064	0.0629	**0.1819**
Line 30	0	0.0016	0.0494	**0.1637**
Line 38	0	0.0001	0.0387	**0.1387**

TABLE 3-6- PROBABILITY OF FAILURE FOR DIFFERENT COMPONENTS IN HURRICANE PATH 3.

	Category			
	1 & 2	3	4	5
Line 5	**0.3875**	**0.4541**	**0.3802**	**0.3053**
Line 6	0.0862	**0.3082**	**0.3395**	**0.3057**
Line 7	0.0629	**0.2769**	**0.3312**	**0.3032**
Line 18	0	0.0583	**0.2253**	**0.2544**
Line 19	0	0.0758	**0.2442**	**0.2638**
Line 21	0	0.0032	0.085	**0.1698**
Line 15	0	0.0008	0.0617	**0.1489**
Line 29	0	0	0.0393	**0.1255**

Table 3-7 shows the system operation cost and the load curtailment (LC) in each contingency scenario obtained from solving the SCUC problem based on the identified outages. As the same commitment is used for each number of components on outage (*m*), the total operation cost is constant. However, the results indicate that by increasing the number of simultaneous component outages, the load curtailment increases drastically. For larger amounts of outage i.e. hurricane category 5, the SCUC problem is not able to find a feasible solution. The results indicate that although the *N*-1 criterion is suitable for ensuring power system security in daily operation, but it does not provide a viable solution when dealing with extreme events and multiple component outages.

TABLE 3-7- OPERATION COST AND LOAD CURTAILMENT OF N-1 SCUC FOR DIFFERENT HURRICANE CATEGORIES

Hurricane Category	Total Cost	LC Scenario 1 (MWh)	LC Scenario 2 (MWh)	LC Scenario 3 (MWh)
1&2	$10,730	0	0	0
3	$10,730	145	128	128
4	$10,730	237	528	128
5	-	-	-	-

3.2.3. Proposed E-SCUC

In this case, the proposed E-SCUC is used to find optimal scheduling of the simultaneous outage of multiple components along with the *N*-1 reliability criterion. Particularly, 50 scenarios is defined, 47 scenarios representing the single component outage (*N*-1) and 3 representing outage scenarios for each path of the hurricane (*N-1-m*). Component outages along each hurricane path are the same as components that are studied in Case 2 (shown bold in Table 3-4, Table 3-5, and Table 3-6). Table 3-8 shows the system operation cost and the load curtailment in each contingency scenario obtained as the E-SCUC solution. In addition, the cost increase and average load curtailment decrease compared to the SCUC with *N-m* reliability criterion (Case 2) are shown in Table 3-8.

TABLE 3-8- OPERATION COST AND LOAD CURTAILMENT OF THE PROPOSED E-SCUC FOR STUDIED SCENARIOS

Category	Total Cost	Cost Increase	LC S1 (MWh)	LC S2 (MWh)	LC S3 (MWh)	Avg. LC Decrease
1&2	$10,759	0.26%	0	0	0	0%
3	$10,847	1.09%	0	0	0	100%
4	$10,937	1.92%	0	87	42	85%
5	$10,943	-	318	373	862	-

The obtained results advocate that for more destructive categories of hurricane (where the number of simultaneous component outages increases), the operation cost increases, evidently due to the increased number of components that need to be committed in the normal operation and used in contingencies. Comparing the results of

E-SCUC with SCUC (Case 2) indicates that the proposed E-SCUC model is more resilient against multiple simultaneous component outages as the amount of load curtailment is considerably lower than SCUC problem under similar contingency scenarios. As an example, the load curtailment in response to a category 3 hurricane is reduced to zero when the proposed E-SCUC is utilized.

3.3. Role of Microgrids in Power System Resilience

The proposed optimal microgrid placement model is applied to the standard IEEE 118-bus test system ("IEEE 118-Bus System - Illinois Center for a Smarter Electric Grid (ICSEG)," n.d.). It is assumed that a hurricane passes through the system under three path/intensity scenarios as shown in Figure 3-3. Since the probability and severity of hurricanes from the southwest side of the system are higher compared to those of hurricanes from other directions, only this section of the system is shown in Figure 3-3. The outage probability of components in the path of hurricanes is calculated based on the available hurricane data and maximum wind gust speed that the components can withstand (Lu and Garrido 2005), where those with higher probabilities are selected. The number of components on outage is changed from 1 to 9 in order to be able to compare the results. Table 3-9 represents the components that are potentially damaged. The annual peak load in the system is 3733 MW. For simplification, the hourly changes in the load are not considered, and the load is divided into three levels of peak load (3733 MW), intermediate load (3241 MW), and base load (2749 MW). The VOLL at all buses and ratio of the load supplied by microgrids, i.e., k, are considered to be \$10,000/MWh and

10%, respectively. The microgrids capital cost and total investment budget are considered to be \$1.5 million per MW and \$70 million, respectively. The problem is formulated by mixed-integer programming (MIP) and solved by CPLEX 12.6 (“CPLEX 12, IBM ILOG CPLEX, User’s Manual, 2013,” n.d.)i. Following cases are studied:

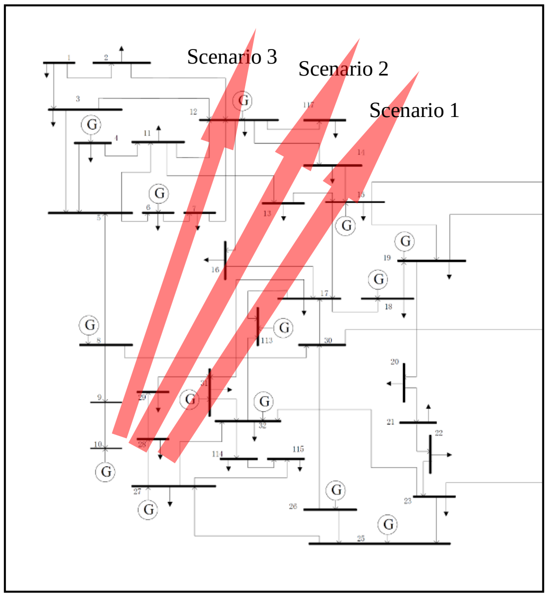

FIGURE 3-3- IEEE 118-BUS TEST SYSTEM AND THE FORECASTED HURRICANE PASSING THROUGH THREE HYPOTHETICAL PATHS

3.3.1. Without considering microgrids

In this case, the proposed model without considering microgrids is solved. The results are represented in Table 3-10. If there are up to two components on outage, there would not be any load curtailments in the system. By increasing the number of components on outage, the load curtailments, and hence the cost of unserved energy, would increase since the system cannot supply all the loads.

Table 3-9- Simultaneous Components on Outage Along the Hurricane Paths (L: transmission line, G: generation unit)

No. of comp. on outage	Scenario 1	Scenario 2	Scenario 2
1	L33	G12	G4
2	L33,L181	G12, L34,	G4,L35
3	L33,L181,L182	G12, L34, L43	G4,L35,L40
4	L33,L181,L182,L41	G12, L34, L43,L42	G4,L35,L40,L37
5	L33,L181,L182,L41, L25	G12,L34, L43,L42,L37	G4,L35,L40,L37, L39
6	L33,L181,L182,L41, L25,L27	G12,L34,L43,L42, L37,L22	G4,L35,L40,L37, L39,L20
7	L33,L181,L182,L41, L25,L27,L54	G12,L34,L43,L42, L37,L22,L21	G4,L35,L40,L37, L39,L20,L16
8	L33,L181,L182,L41, L25,L27,L54,L46	G12,L34,L43,L42, L37,L22,L21,L26	G4,L35,L40,L37, L39,L20,L16,L17
9	L33,L181,L182,L41, L25,L27,L54,L46,L47	G12,L34,L43,L42, L37,L22,L21,L26,L44	G4,L35,L40,L37,L39,L20,L16,L17,G5

Table 3-10- Load Curtailments Results in Response to Hurricane Scenarios Without Microgrid Installations

No. components on outage	LC Scenario 1 (MW)	LC Scenario 2 (MW)	LC Scenario 3 (MW)	Cost of Unserved Energy ($)
1-2	0	0	0	0
3-5	60.8		66.4	1,271,806
6-8	110.6		66.4	1,769,537
9	201.8		758.5	9,603,675

3.3.2. Installing microgrids in load buses

In this case, it is assumed that microgrids can be installed, in load buses, to help reduce system load curtailments as encountered in Case 0. Table 3-11 summarizes the load curtailments results with respect to outage scenarios, the buses where microgrids are installed, the total installed capacity of microgrids, and the microgrids costs. By having only one component on outage, there is no need to install any microgrids since the load curtailments is zero. By increasing the number of components on outage, microgrids would be installed in affected buses or their adjacent buses. As the number of components on outage increases, microgrids would be installed in more buses, and the microgrids total capacity would increase in order to compensate for the system inability to adequately supply loads. According to Table 3-11, the total load curtailments in the system would increase by increasing the number of components on outage, but it has decreased compared to that in Case 0. It should be noticed that there is not any outage in response to scenario 2, meaning that the direction of the hurricane in scenario 2 is such that the system is completely reliable and would be able to fully supply loads.

3.3.1. The effect of budget on the microgrid capacity and load curtailments

This case discusses the effect of budget on the microgrid installed capacity and load curtailments when all other parameters are kept unchanged. The results of N-9, i.e., 9 components on outage, are represented in Table 3-12. Having the budget of \$20M or \$30M would result in the microgrid installation of 13.3 MW and 20.0 MW, respectively. In these two cases, the maximum possible capacity of microgrids would be installed since the total capital cost is equal to the maximum available budget. By increasing the budget, the microgrid installed capacity would increase too up to 34 MW (associated with the budget of $55M) which acts as a saturation point. In other words, by increasing the budget more than $55M, the total microgrid installation would not change. It is noticeable that although there is an increase in the total microgrid installed capacity by increasing the budget up to $55M, the load curtailments does not change. The reason is that the objective of this model is to minimize the cost of unserved energy, not the capital cost. However, the load curtailments, and thereby the cost of unserved energy, would decrease compared to the base case under N-9 criterion, as shown in Table 3-12.

3.3.1. The effect of changing the ratio of loads supplied by microgrids

In this case, the effect of changing the ratio of loads supplied by microgrids, i.e., *k*, on the system load curtailments under N-9 criterion is studied. The results are summarized in Table 3-13. The parameter *k* is increased by steps of 5%. It is expected that following an increase in the ratio of loads supplied by microgrids, more capacity of microgrids be installed which causes the system load curtailments to reduce. Similar to previous cases, there would not be any load curtailments following the hurricane in scenario 2. It is observable that following the increase in *k*, the cost of unserved energy would significantly reduce compared to the base case with 9 damaged components. The increase in the total microgrid installed capacity would increase the total capital cost such that it reaches the maximum available budget when 25% of the load is supplied by the microgrids.

TABLE 3-11- LOAD CURTAILMENTS RESULTS IN RESPONSE TO HURRICANE SCENARIOS CONSIDERING MICROGRID INSTALLATIONS

No. of comp. on outage	LC Scen. 1 (MW)	LC Scen. 2 (MW)	LC Scen. 3 (MW)	Change in cost of unserved energy (%)	Buses with installed microgrid	Total Installed MG (MW)	Total MG Costs (M$)
1	0	0	0	0	-	0.0	0.0
2	0		0	0	28,29,115	6.7	10.0
3	54.7		59.7	-10.0	28,29, 114,115	7.5	11.3
4					23,28,29, 114,115	8.3	12.4
5					17,20,23,28,29,114,115	11.4	17.0
6	99.5				16,17,20,21,23,28,29, 114,115	15.5	23.2
7					11,13,16,17,20,21,23, 28,29,114, 115	26.5	39.8
8					11,13,14,16,17,20,21, 23,28,29,35,114,115	31.5	47.3
9	181.6		732.5	-4.8	11,13,14,16,17,20,21, 23,28,29,33,35,114,115	34.0	51.0

TABLE 3-12- IMPACT OF THE BUDGET ON THE SYSTEM LOAD CURTAILMENTS

Budget (M$)	LC Scen. 1 (MW)	LC Scen. 2 (MW)	LC Scen. 3 (MW)	Change in cost of unserved energy (%)	Total Installed MG (MW)	Total MG Costs (M$)
20	181.6	0	742.8	-3.7	13.3	20.0
30	181.6	0	732.5	-4.8	20.0	30.0
40	181.6	0	732.5	-4.8	21.8	32.7
50	181.6	0	732.5	-4.8	30.0	44.9
≥55	181.6	0	732.5	-4.8	34.0	51.0

TABLE 3-13- IMPACT OF THE RATIO OF LOADS SUPPLIED BY MICROGRIDS ON THE SYSTEM LOAD CURTAILMENTS

k	LC Scen. 1 (MW)	LC Scen. 2 (MW)	LC Scen. 3 (MW)	Change in cost of unserved energy (%)	Total Installed MG (MW)	Total MG Costs (M$)
0.00	201.8	0	758.5	0.0	0.0	0
0.05	191.7		745.5	-2.4	17.0	25.5
0.10	181.6		732.5	-4.8	34.0	51.0
0.15	171.6		719.6	-7.2	37.1	55.7
0.20	161.5		706.6	-9.6	43.3	65.0
0.25	151.4		693.6	-12.0	46.7	70.0

4. CHAPTER FOUR: CONCLUSION

Resilience in response to extreme events is one the most important aspects of power systems. SCUC is commonly used for scheduling available generation resources to satisfy the forecasted load in response to limited components unavailability.

In this thesis, an Event-driven SCUC model was proposed and developed to consider the simultaneous outage of several system components, representing an N-1-m reliability criterion. The numerical simulations on the standard IEEE 30-test system exhibited the merits and applicability of the proposed E-SCUC model in ensuring an economic operation under normal conditions and a resilient operation under contingency cases. Comparing the results of the proposed E-SCUC with the SCUC indicated that the proposed E-SCUC method is more resilient against multiple component outages. In particular, it can reduce the amount of load curtailment (~50%) compared to the SCUC problem, while resulting in a small cost increase (~5%). This survey studied hurricanes as a common form of extreme events. The proposed models, however, could be extended and applied to other types of extreme events with minimum adjustments.

The proposed event-driven security-constrained unit commitment (E-SCUC) model was further studied by considering the simultaneous outages of several system components, representing an N-1-m reliability criterion. A KDE method, based on regression and data mining, was used to estimate and model the system components that will likely fail due to a predicted hurricane. An artificial set of data was generated in this study to estimate the probability of the component outages, as the publicly available data on the impact of hurricanes on power system components is limited. The proposed KDE approach is a general framework, which can ensure more accurate estimations if it is trained on extensive historical data from storm-related damages and their impacts on the system components. The numerical simulations on the standard IEEE 30-bus test system illustrated the merits and applicability of the proposed E-SCUC model. Comparison of the results of the proposed E-SCUC with those from the conventional SCUC without the events modeled indicated that the proposed E-SCUC method can produce a more robust solution that can protect the system against multiple component outages due to a hurricane.

Finally, an optimal microgrid placement model to enhance power system resilience was proposed. The objective was to minimize the cost of unserved energy following hurricanes. For developing proper scenarios to model the impact of hurricanes on component outages, the probabilistic failure model of the system components was considered. The problem was formulated by MIP, solved by CPLEX, and applied to the standard IEEE 118-bus test system. It was shown that installing microgrids in proper locations would significantly increase the system resilience by reducing the load curtailments during contingency scenarios. It was demonstrated that increasing the budget would allow for installing a larger microgrid capacity, hence reducing the cost of unserved energy, while reaching a saturation point after certain budgets. It was further shown that increasing the ratio of the loads supplied by microgrids would significantly reduce the total load curtailments due to the capability of installing larger microgrid capacities.

5. REFERENCES

Abiri-Jahromi, Amir, Masood Parvania, Francois Bouffard, and Mahmud Fotuhi-Firuzabad. 2013. "A Two-Stage Framework for Power Transformer Asset Maintenance management—Part I: Models and Formulations." *Power Systems, IEEE Transactions on* 28 (2): 1395–1403.

Arab, Ali, Amin Khodaei, Zhu Han, and Suresh K. Khator. 2015. "Proactive Recovery of Electric Power Assets for Resiliency Enhancement." *Access, IEEE* 3: 99–109.

Arab, Ali, Amin Khodaei, Suresh K. Khator, Kevin Ding, Valentine Emesih, Zhu Han, and others. 2015. "Stochastic Pre-Hurricane Restoration Planning for Electric Power Systems Infrastructure." *Smart Grid, IEEE Transactions on* 6 (2): 1046–1054.

Arab, Ali, Eylem Tekin, Amin Khodaei, Suresh K. Khator, and Zhu Han. 2014. "Dynamic Maintenance Scheduling for Power Systems Incorporating Hurricane Effects." In *Smart Grid Communications (SmartGridComm), 2014 IEEE International Conference on*, 85–90. IEEE.

Attoh-Okine, Nii O., Adrienne T. Cooper, Stephen Mensah, and others. 2009. "Formulation of Resilience Index of Urban Infrastructure Using Belief Functions." *Systems Journal, IEEE* 3 (2): 147–153.

Ball, Billy. 2006. "Rebuilding Electrical Infrastructure along the Gulf Coast: A Case Study." *BRIDGE-WASHINGTON-NATIONAL ACADEMY OF ENGINEERING-* 36 (1): 21.

Billinton, Roy, and Peng Wang. 1999. "Teaching Distribution System Reliability Evaluation Using Monte Carlo Simulation." *Power Systems, IEEE Transactions on* 14 (2): 397–403.

Brown, R. E. 2009. "Cost-Benefit Analysis of the Deployment of Utility Infrastructure Upgrades and Storm Hardening Programs." *Quanta Technology, Raleigh*.

Cano-Andrade, Sergio, Michael R. von Spakovsky, Alejandro Fuentes, Chiara Lo Prete, Benjamin F. Hobbs, and Lamine Mili. 2012. "Multi-Objective Optimization for the Sustainable-Resilient Synthesis/Design/Operation of a Power Network Coupled to Distributed Power Producers via Microgrids." In *ASME 2012 International Mechanical Engineering Congress and Exposition*, 1393–1408. American Society of Mechanical Engineers.

Che, Liang, and Mohammad Shahidehpour. 2014. “DC Microgrids: Economic Operation and Enhancement of Resilience by Hierarchical Control.” *Smart Grid, IEEE Transactions on* 5 (5): 2517–2526.

“CPLEX 12, IBM ILOG CPLEX, User’s Manual, 2013.” n.d. http://gams.com/dd/docs/solvers/cplex.pdf.

Davidson, Rachel A., Haibin Liu, Isaac K. Sarpong, Peter Sparks, and David V. Rosowsky. 2003. “Electric Power Distribution System Performance in Carolina Hurricanes.” *Natural Hazards Review* 4 (1): 36–45.

Economics, London. 2013. “Estimating the Value of Lost Load.” *Briefing Paper Prepared for ERCOT (17 June 2013)*.

Executive Office of the President. 2015. “Economic Benefits of Increasing Electric Grid Resilience to Weather Outages-August 2013.” Accessed June 14.

Guidoum, Arsalane Chouaib. 2013. “Kernel Estimator and Bandwidth Selection for Density and Its Derivatives.”

Guikema, Seth David, Roshanak Nateghi, Steven M. Quiring, Andrea Staid, Allison C. Reilly, and Ming-Liang Gao. 2014. “Predicting Hurricane Power Outages to Support Storm Response Planning.” *Access, IEEE* 2: 1364–1373.

Huser, Raphaël, and A. C. Davison. 2014. “Space–time Modelling of Extreme Events.” *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 76 (2): 439–461.

“IEEE 30-Bus System - Illinois Center for a Smarter Electric Grid (ICSEG).” n.d. http://icseg.iti.illinois.edu/ieee-30-bus-system/.

“IEEE 118-Bus System - Illinois Center for a Smarter Electric Grid (ICSEG).” n.d. http://publish.illinois.edu/smartergrid/ieee-118-bus-system/.

Karl, Thomas R. 2009. *Global Climate Change Impacts in the United States*. Cambridge University Press.

Khodaei, Amin. 2014. “Resiliency-Oriented Microgrid Optimal Scheduling.” *Smart Grid, IEEE Transactions on* 5 (4): 1584–1591.

Lotfi, H., and A. Khodaei. 2015. “AC Versus DC Microgrid Planning.” *IEEE Transactions on Smart Grid* PP (99): 1–1. doi:10.1109/TSG.2015.2457910.

Lu, Yi, and José Garrido. 2005. “Doubly Periodic Non-Homogeneous Poisson Models for Hurricane Data.” *Statistical Methodology* 2 (1): 17–35.

Nateghi, Roshanak, Seth D. Guikema, and Steven M. Quiring. 2011. “Comparison and Validation of Statistical Methods for Predicting Power Outage Durations in the Event of Hurricanes.” *Risk Analysis* 31 (12): 1897–1906.

Nateghi, Roshanak, Seth D Guikema, and Steven M Quiring. 2014. “Forecasting Hurricane-Induced Power Outage Durations.” In *Natural Hazards*, 74:1795–1811.

Paaso, Esa Aleksi, Yuan Liao, and Aaron M. Cramer. 2015. “Dual-Layer Voltage and VAR Control Approach with Active Participation from Distributed Solar Generations.” *Electric Power Components and Systems* 43 (8–10): 854–865.

Paaso, Esa Aleksi, Joseph E. Svachula, and Shay Bahramirad. 2015. “Planning and Operations of the Utility of the Future in Illinois.” *The Electricity Journal* 28 (10): 18–28.

Parhizi, Sina, Hossein Lotfi, Amin Khodaei, and Shay Bahramirad. 2015. “State of the Art in Research on Microgrids: A Review.” *IEEE Access* 3: 890–925. doi:10.1109/ACCESS.2015.2443119.

Parzen, Emanuel. 1962. “On Estimation of a Probability Density Function and Mode.” *The Annals of Mathematical Statistics* 33 (3): 1065–1076.

Reed, Dorothy A. 2008. “Electric Utility Distribution Analysis for Extreme Winds.” *Journal of Wind Engineering and Industrial Aerodynamics* 96 (1): 123–140.

Reed, Dorothy A., Kailash C. Kapur, and Richard D. Christie. 2009. “Methodology for Assessing the Resilience of Networked Infrastructure.” *Systems Journal, IEEE* 3 (2): 174–180.

Reed, Dorothy, Kailash C. Kapur, Richard D. Christie, and others. 2009. “Methodology for Assessing the Resilience of Networked Infrastructure.” *Systems Journal, IEEE* 3 (2): 174–180.

Russell, Larry R., Gerhart I. Schueller, and others. 1974. “Probabilistic Models for Texas Gulf Coast Hurricane Occurrences.” *Journal of Petroleum Technology* 26 (3): 279–288.

Schott, Timothy, Chris Landsea, Gene Hafele, Jeffrey Lorens, Arthur Taylor, Harvey Thurm, Bill Ward, Mark Willis, and Walt Zaleski. 2012. “The Saffir-Simpson Hurricane Wind Scale.” *National Weather Services*.

Shahidehpour, Mohammad. 2010. “Role of Smart Microgrid in a Perfect Power System.” In *Power and Energy Society General Meeting, 2010 IEEE,* 1–1. IEEE.

Smith, Richard L. 1990. “Max-Stable Processes and Spatial Extremes.” *Unpublished Manuscript, Univer*.

Wand, Matt P., and M. Chris Jones. 1994. *Kernel Smoothing*. Crc Press.

Winkler, James, Leonardo Duenas-Osorio, Robert Stein, and Devika Subramanian. 2010. "Performance Assessment of Topologically Diverse Power Systems Subjected to Hurricane Events." *Reliability Engineering & System Safety* 95 (4): 323–336.

Xu, Xufeng, Joydeep Mitra, Niannian Cai, and Longhua Mou. 2014. "Planning of Reliable Microgrids in the Presence of Random and Catastrophic Events." *International Transactions on Electrical Energy Systems* 24 (8): 1151–1167.

Zhu, Yihai, Jun Yan, Yufei Tang, Yan Lindsay Sun, and Haibo He. 2014. "Resilience Analysis of Power Grids under the Sequential Attack." *Information Forensics and Security, IEEE Transactions on* 9 (12): 2340–2354.

Zhuang, Jiancang, Yosihiko Ogata, and David Vere-Jones. 2002. "Stochastic Declustering of Space-Time Earthquake Occurrences." *Journal of the American Statistical Association* 97 (458): 369–380.

6. APPENDIX 1 - PUBLICATIONS

1. R. Eskandarpour, A. Khodaei, and Jeremy Lin. "Event-Driven Security-Constrained Unit Commitment," *IEEE PES Innovative Smart Grid Technologies Conference,* Minneapolis, MN, September 2016.

2. R. Eskandarpour, A. Khodaei, and Jeremy Lin. "Event-Driven Security-Constrained Unit Commitment with Machine Learning based Outage Estimation". *North American Power Symposium* 2016.

3. R. Eskandarpour, H. Lotfi, A. Khodaei. "Optimal Microgrid Placement for Enhancing Power System Resilience in Response to Weather Events". *North American Power Symposium* 2016.

4. R. Eskandarpour, G. Edwards, A. Khodaei. "Resilience-Constrained Unit Commitment Considering the Impact of Microgrids". *North American Power Symposium* 2016.

5. R. Eskandarpour, A. Khodaei, "Predicting Power Grid Component Outage In Response to Extreme Events", *CIGRE US National Committee, Grid of the Future Symposium,* 2016

6. R. Eskandarpour, A. Khodaei, "Machine Learning based Power Grid Outage Prediction in Response to Extreme Events", *IEEE Power Engineering Letters*, 2016